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Predicting numbers of successful new products to launch using soft computing techniques: A case of firms from manufacturing sector industries

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ABSTRACT

Predicting numbers of new products to be launched by the firms in a particular time period is considered as the most mystified and strategically important decision. Importance of this aspect could be realized by looking at the low success rate of new products in the market. Identifying numbers of new products potentially accepted by the market may reduce the investment and scant resources consumption by firms. In this study, statistical multiple linear regression, and artificial neural network techniques modeled as simple and cascaded networks combined with nature inspired algorithm have been implemented. Artificial neural network has shown significant performance results and further cascading helps in enhancing the prediction accuracy along with better convergence capability of the developed models for the predicament.

1. Introduction

Product which gives an essence of something new or different from the existing product could be defined as the new product. Developing a new product requires a lot of investment in terms of finance, human resource, infrastructure etc. All new products launched were not able to end doing well in the market. A study made by product development and management association (PDMA) states that approximately half of the new products launched failed to mark their presence in the market. Predicting accurately successful numbers of new products to be launched in a particular time frame is a challenging task for the top level management of any firm. Launching new product is directly related to new product development which turns out to be a function of many variables. Developing new product could not be possible in isolation since many internal and external factors to the firm contribute in the development process (Dempster, 1971). Pace of developing new products may possibly be estimated by identifying critically important parameters specific to firms. Focus of this study is on the firms belonging to the manufacturing sector. Innovativeness in this sector could be seen as the rate of development of new products. The high rate of new product development has cultivated revolutionary environment in the market. Dynamicity of this sector makes it difficult to match acceptance rate of new products in the market with the rate of new product development, resulting in higher rate of new product failures. Acknowledging this scenario crucially important parameters have been identified from intensive literature survey available for new product development under this sector. Data have been collected on the identified parameters (independent/input variables) and corresponding numbers of successful new products (dependent/output variable) launched in three years by the firms fallen under industries, electronics, garment and metal & machinery from manufacturing sector.

Statistical and artificial neural network (ANN) techniques have been used in this study. Multiple linear regression is a method to find the linear relationship between one dependent/output and many independent/input variables often using least square

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approach. ANN techniques were developed by imitating the working of human brain. Basic structure of ANN is composed of neurons and weights associated with them arranged in a definite manner, learning algorithm and an activation function. Functional linked artificial neural network (FLANN) is a variant of ANN which involves less computational load as compared to other ANNs without compromising on the performance efficiency and with the added benefit of its simple structure. Non linearity can be easily inserted in FLANN with the usage of non-linear functional expansions in its basic structure. The basic structure of FLANN is shown in Fig. 2. Some of the most widely used non-linear functional expansions are power, trigonometric, legendre, chebyshev and polynomial series. Numbers of learning algorithms have been developed to work with ANN like least mean square (LMS), recursive least square (RLS), nature inspired techniques e.g. evolutionary algorithm (EA), swarm optimization (SO) and many more. Particle swarm optimization (PSO) is the variant of swarm optimization algorithm that have been implemented in this study other than LMS and RLS learning algorithm. FLANN with power series functional expansion is considered as the basic structure of ANN to study this predicament because of its better performance in comparison to other expansions.

Cascading of neural network is the approach of keeping the exact processing unit at the output terminal of first processing unit. Generally cascading helps in reducing the propagation of error and provides better result than single processing unit. Three possible cascaded configurations have been implemented using different input combinations to cascaded unit. Average MAPE (mean absolute percentage error), RMSE (root mean square error) and STDEV (standard deviation) values obtained using K-fold cross validation for all the FLANN models are summarized in Tables 5, 6 and 7. Statistics obtained from multiple linear regression model is shown in Table 8 and 9. At last managerial implementation and future direction to extend the study have been discussed.

2. Literature review

New product development (NPD) is a chosen topic of research by scientists and researchers from a long time. It has gained a lot of attention from government as well as from business houses / entrepreneurs in last few years because of the tremendous growth in technology and liberal business policies (Wengenroth, 2000). The success rate of new product development should really be of great concern to the firms as about half of new products were withdrawn from the market just after introducing them (Griffin, 1997). NPD process does depend on many internal and external factors specific to firms. Firms belonging to manufacturing sector have some common crucial and important parameters those may help in specifying the pace of development of new products. Many researchers have contributed in this field by identifying such parameters and preparing models for estimating and improving new product development process. Cutting down risk factors associated with the production and to strive for knowledge management either internal or external to firm is an important factor to improve the quality of new product Cooper (2003). Market information plays a vital role in all the three phases of development of product i.e., before development phase, development phase, and commercialization phase and has potential to change the outcome for the product in market (Veldhuizen et al., 2006). An empirical study suggests that speeding up innovation could lead to quality products (Kessler and Bierly, 2002). Holistic networking in knowledge management and development process specific to product is of immense help in development of new products (Chen et al., 2008). Physical location and functional team composition are considered as the main factors in increasing pace while keeping lower error rate for NPD process (Kim and Kim, 2009). A conceptual model has been developed for commercializing new products made by using new technologies (Cho and Lee, 2013). A contingency model have been designed using transaction cost to define the impact of seller and buyer interactions on product customization and shown that joint (buyer and seller) NPD may achieve higher satisfaction level in customers by decreasing the negative effect of product customization (Stump et al., 2002). A relatively easy wait for turn model involving design tasks has been developed by considering four factors novelty in technology, enormity of task involved in designing, extent of connectivity between different tasks and making linkage between jobs using Kolmogorov Smirnov test (Dragut and Bertrand, 2008). Relationship modelling has been established between personality traits of the leader and the type of NPD projects (Aronson et al., 2006). Cost involved in critical design and resource sourcing are important decisions to make by the firm since they play decisive role in costing of product for the market. A substantive model have been proposed which says that cost incurred in sourcing decisions plays a significant role in overall cost reduction of the product (Wouters et al., 2009). A model has been suggested using support vector mechanism and imperialist competitive algorithm to estimate the time duration for the NPD projects (Meysam Mousavi et al., 2013). New product should be developed according to firms' capacity and strength. A fuzzy linear programming model has been developed using quality function deployment in four phases taking risk as a constraint for NPD (Chen and Ko, 2010). ANN techniques have been used to understand the development of process for product development using information analysis and demonstrated that it could help in reducing time, cost and the risk associated with it (Chen et al., 1998). On the basis of fuzzy analytical hierarchy procedure as well as on fuzzy data envelope analysis along with Bayesian belief network as a constraint to compensate for risk factors, a model has been developed to rank the NPD projects (Chiang and Che, 2010). Choosing one from various top ranked promising projects for NPD in itself is a big task. To resolve this a system has been suggested whose basis is ANN to select one particular project and it is observed that for given dataset neural network can able to predict about 96.7% correctly the project which actually going to be success (Thieme et al., 2000). Comparison between logistic regression. discriminant analysis and back propagated neural network model have been made and results were in favour of neural network with marginal difference (Dasgupta et al., 1994). Econometric test and neural network modelling have been done to forecast the consumers' expenditure and result showed that success of analysis depends on the choices made for explanatory variables (Church and Curram, 1996).

3. Data collection and validation

Data have been collected from numbers of firms belonging to electronics, garment and metal & machinery industries pertaining to different regions (locations) on critically important parameters identified from literature survey. These parameters affect the new product development process either directly or in an indirect manner. The nine parameters identified are provided in Table 1 and considered as independent variables for the analysis. Data from 398 electronics firms have been collected and after removing outliers and missing values 327 firms' data were used for the analysis. Similarly, for garment industry 751 firms provide data but only 445 firms' data were used in analysis because of huge number of missing values and for metal & machinery firms, 663 firms have given data but only 464 firms' data were used.

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4. Research methodology

The flowchart depicting the steps involved in the analysis is shown in Fig. 1. The Validated data needs to be normalized and randomized before using as input. Normalization ensures that all input variables are on same scale and randomization helps in robust building of the developed model. The developed models are trained and tested using **K-fold scheme where K is taken as 10**. Multiple linear regression and neural network techniques models have been developed and tested using MATLAB **R2011b** analytic tool package on **intel(R) Core(TM) i5-3337 CPU@1.80 GHz running 64 bit Windows 8 operating system with 4 GB RAM (installed)**. Equations involved in developing different models have been provided in model development section. The results obtained from different models have been tabulated in Tables 5, 6, 7, 8 and 9. Average MAPE and RMSE values obtained from 10-fold simulations were used as the performance measure indices for the developed neural network models. In case of multiple linear regression model R-square and adjusted R-square values were considered to find out mapping efficiency between dependent and independent variables. Lower value of MAPE and RMSE suggest that model is performing well as compared to other developed

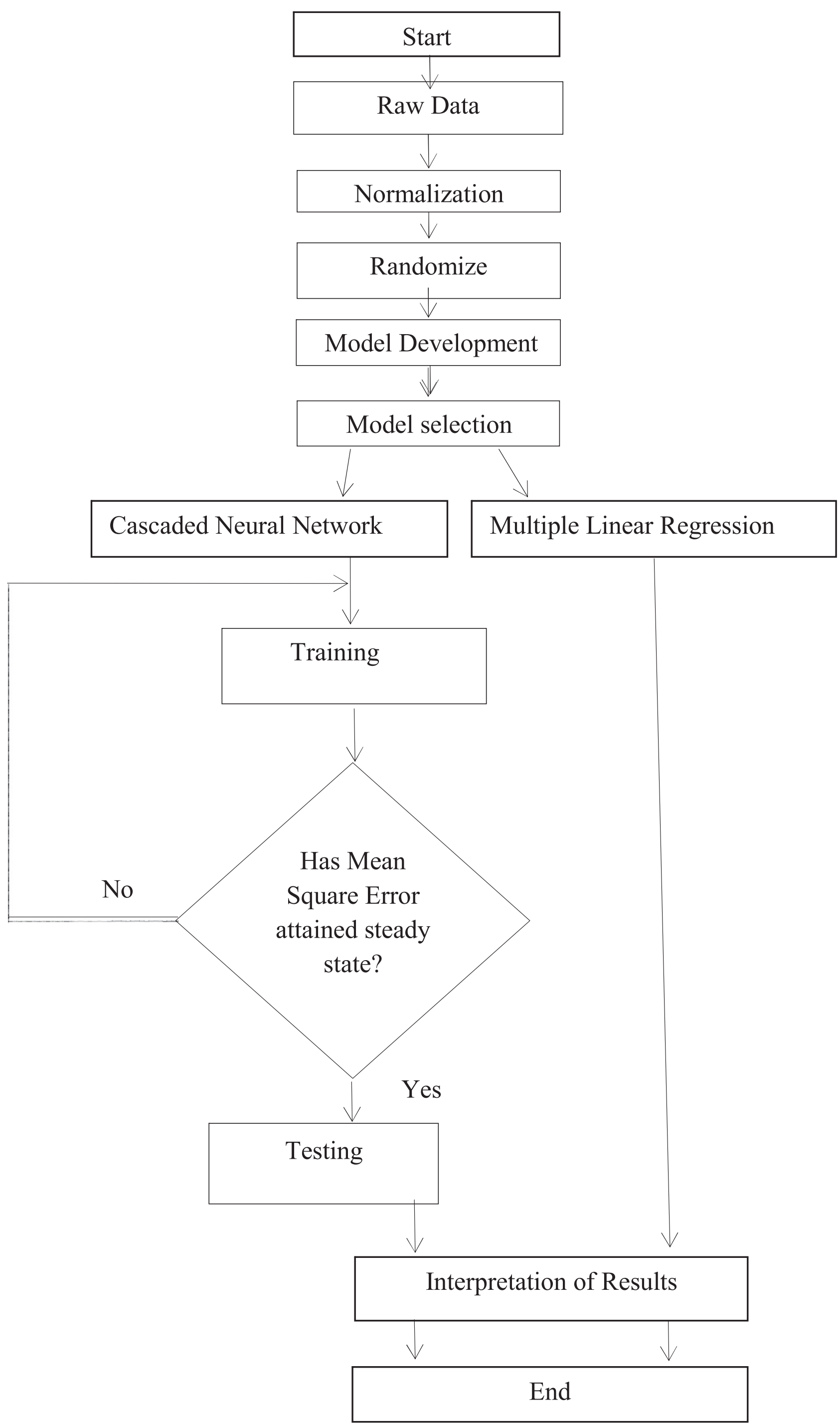

Fig. 1. Different steps involved in analysis.

Table 1
Variables used in the analysis.

Dependent Variable	Independent Variables
New products ($Y_{(r,\ 1)}$)	Numbers of years firm has completed from its establishment (x_1) (Naldi and Davidsson, 2014) Numbers of years firm is involved in exporting (x2) (Glick, 1982) Numbers of permanent employees (x3) (Bourgeon, 2007) Gross National Income (GNI) of country where firm operates (x4) (Roessner et al., 2013) Yearly expenditure on product development (x5) (Tsai et al., 2011) Sales amount realized in a year (x6) (McDougall, 1989) Technology used for production (x7) (Xu et al., 2012) Percentage of supplies from domestic market (x8) (Zhang and Wu, 2016) Total number of products produced by the firm (x9) (Frankenhoff and Granger, 1971)

models having higher value of MAPE and RMSE for a particular case under study. However, for multiple linear regression higher the value and R-square and adjusted R-square suggests the phenomenon under study has been mapped efficiently and there exist a linear relationship between dependent and independent variables.

5. Basic neural network model development

The basic neural network modelling was first done by Klopf, Barton, Sutton, Grossberg, and Freeman in 1960s (Greenwood, 1991). Neural network techniques could be used to model different phenomenon (Majhi et al., 2006, 2009; Gosasang et al., 2011) by learning from the past data applied to it (Haykin and Gwynn, 2008). FLANN is a single layered ANN developed by Pao (1989) using only one neuron. Single layered structure of FLANN made it to do fewer computations as compared to other traditional neural networks and results in faster convergence rate (Patra et al., 1999). Non-linear phenomenon could be studied well using FLANN because of inherent non-linearity in its structure which is not possible in the case of linear multiple regression where only linear mapping is feasible for different variables under consideration. In view of inherent non-linear nature of new product development (Hagan et al., 2014) FLANN models have been developed for analysis. Three conventional functional expansions; trigonometric, chebyshev and legendre (Lippmann, 1987; Masters, 2014) along with power series expansion have been used with FLANN structure. Adaptive prediction algorithms are globally convergent and ensure stability if a capricious feedback has been applied between input and output of the model (Goodwin et al., 1981). Least mean square (LMS) (Widrow et al., 1985), recursive least squares (RLS) (Sachdev and Nagpal, 1991) and particle swarm optimization (PSO) algorithms (Kennedy and Eberhart, 1995; Feng et al., 2017; Amirthalingam and Radhamani, 2016; Kim et al., 2017) are employed in the analysis to update the weights assigned to each expanded input. The results obtained for power series expansion is better than any other functional expansions embedded with FLANN models and have been reported in Tables 2, 3 and 4.

Simple block diagram for FLANN model is shown in Fig. 2. Inputs consist of values for different factors affecting development of new products of the firms considered under study. Output of model is the predicted numbers of new products developed by the corresponding firms.

Each element of an input vector is applied to non- linear functional expansion block and a new pattern of input vector with an increase in its dimensionality is generated. Random weights are assigned and initialized to every expanded input of the input vec-

Table 2
Parameters used for FLANN-LMS configuration.

Parameter used	Value
Common for both units	
Numbers of iterations	1000
Learning factor	0.01
Type of nonlinear expansion	Power series
Numbers of expansions	3
Activation function	Hyperbolic Tangent
Unit-1	
Bias weight	Yes
Numbers of weights	27
Unit-2 (Case-1)	
Bias weight	Yes
Numbers of weights	3
Unit-2 (Case-2)	
Bias weight	No
Numbers of weights	30
Unit-2 (Case-3)	
Bias weight	Yes
Numbers of weights	30

Table 3
Parameters used for FLANN-RLS configuration.

Parameter used	Value
Common for both units	
Numbers of iterations	1000
Forgetting factor	0.99
Type of nonlinear expansion	Power series
Numbers of expansions	3
Activation function	Hyperbolic Tangent
Unit-1	
Bias weight	Yes
Numbers of weights	27
Unit-2 (Case-1)	
Numbers of Bias weight	Yes
Numbers of weights	3
Unit-2 (Case-2)	
Bias weight	No
Numbers of weights	30
Unit-2 (Case-3)	
Bias weight	Yes
Numbers of weights	30

Table 4
Parameters used for FLANN-PSO configuration.

Parameter used	Value
Common for both units	
Numbers of iterations	200
Population size	50
Constant C1 and C2	1.042
Type of nonlinear expansion	Power series
Numbers of expansions	3
Activation function	Hyperbolic Tangent
Unit-1	
Bias weight	Yes
Numbers of weights	27
Unit-2 (Case-1)	
Bias weight	Yes
Numbers of weights	3
Unit-2 (Case-2)	
Bias weight	No
Numbers of weights	30
Unit-2 (Case-3)	
Bias weight	Yes
Numbers of weights	30

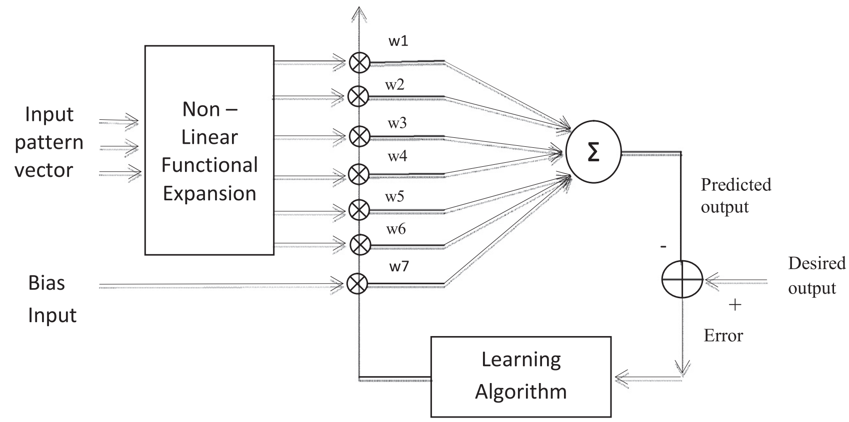

Fig. 2. Block Diagram of FLANN model.

Table 5
Cascaded FLANN-LMS model with three different input combinations to cascaded unit using 10-fold cross validation.

LMS		Industry		Electronics	Garment	Metal & Machinery
Type and number of expansions in first unit		Power series with 3 number of expansions per input				
Type and number of expansions in cascaded unit		Power series with 3 number of expansions per input				
Unit-1	Expanded input with bias	MAPE	Training	5.9715	2.9492	3.3546
			Testing	6.2392	3.9728	4.0747
		RMSE	Training	0.0857	0.0474	0.0559
			Testing	0.0911	0.0512	0.0582
		STDEV	Training	0.0547	0.0314	0.0385
			Testing	0.0585	0.0491	0.0405
Unit-2 (Case-1)	Expanded output with bias to cascaded unit	MAPE	Training	**5.5352**	**2.4454**	**3.0232**
			Testing	**5.8458**	**3.1269**	**3.2941**
		RMSE	Training	**0.0757**	**0.0367**	**0.0453**
			Testing	**0.0760**	**0.0393**	**0.0491**
		STDEV	Training	**0.0175**	**0.0435**	**0.0144**
			Testing	**0.0242**	**0.0921**	**0.0156**
Unit-2 (Case -2)	Expanded input and expanded output of first unit to cascaded unit	MAPE	Training	5.6423	2.9264	3.2187
			Testing	5.9616	3.3265	3.8147
		RMSE	Training	0.0814	0.0454	0.0532
			Testing	0.0951	0.0472	0.0405
		STDEV	Training	0.0351	0.0414	0.0332
			Testing	0.0484	0.0435	0.0234
Unit-2 (Case-3)	Expanded input and expanded output of first unit with bias to cascaded unit	MAPE	Training	5.5694	2.7432	3.3163
			Testing	5.9317	3.6355	3.9338
		RMSE	Training	0.0781	0.0451	0.0469
			Testing	0.0803	0.0504	0.0480
		STDEV	Training	0.0376	0.0352	0.0338
			Testing	0.0391	0.0214	0.0450

Best simulation results obtained corresponding to the developed model have been shown as bold values.

tor. The weighted new input vector is summed up and passed through the activation function to get the estimated numbers of new products. Estimating error is calculated by subtracting predicted values from actual values for numbers of new products. Learning algorithm uses this error value to update the weights. The weights are continuously updated using K-fold method until the root mean square error (*RMSE*) for the model attains steady state. The resulting weights are referred as optimum weights and the period until the optimum weights are achieved is referred as training period. After obtaining optimum weights the model is set to provide its best performance. During testing phase mean absolute percentage error (*MAPE*) is calculated using the testing samples and used as the performance measurement index. **Also, standard deviation *(STDEV)* has been calculated for each model implemented in this study**. An average value of MSE, MAPE and STDEV has been obtained by k-fold (k = 10) simulations and results are reported in Tables 5, 6 and 7.

5.1. Cascaded neural nerwork model development

The block diagram for general cascaded network has been shown in Fig. 3. In this study analysis of the cascaded FLANN model with power series expansion is discussed using LMS, RLS, and PSO weight updating algorithms.

Cascaded neural networks have been reported in many forecasting (Zhang et al., 2003; AlFuhaid et al., 1997; Majhi et al., 2007) and classification (Lin et al., 2000; Huang et al., 2003) problems. Cascaded neural networks have shown better performance as compared to other counterpart techniques. In this study, three cases of cascaded neural networks have been configured on the basis of input to the second unit and have been shown in Fig. 4. In first case, output from the first unit becomes input for the second unit and a bias signal is provided separately. For second case, same input pattern which was provided to the first unit is applied to the second unit along with the output of first unit. In third and

Table 6
Cascaded FLANN-RLS model with three different input combinations to cascaded unit using 10-fold cross validation.

RLS		Industry		Electronics	Garment	Metal & Machinery
Type and number of expansions in first unit		Power series with 3 number of expansions per input				
Type and number of expansions in cascaded unit		Power series with 3 number of expansions per input				
Unit-1	Expanded input with bias	MAPE	Training	5.9851	3.9975	3.8842
			Testing	6.7482	5.1682	3.8945
		RMSE	Training	0.0781	0.0486	0.0473
			Testing	0.1138	0.1860	0.0836
		STDEV	Training	0.0244	0.0283	0.0157
			Testing	0.0247	0.0302	0.0228
Unit-2 (Case-1)	Expanded output with bias to cascaded unit	MAPE	Training	**5.2314**	**3.7581**	**3.3510**
			Testing	**5.5517**	**4.8624**	**3.4862**
		RMSE	Training	**0.0683**	**0.0483**	**0.0453**
			Testing	**0.0828**	**0.1765**	**0.0748**
		STDEV	Training	**0.0251**	**0.0281**	**0.0146**
			Testing	**0.0258**	**0.0298**	**0.0224**
Unit-2 (Case-2)	Expanded input and expanded output of first unit to cascaded unit	MAPE	Training	5.4524	4.0532	3.7643
			Testing	6.0413	4.9799	3.7830
		RMSE	Training	0.0721	0.0494	0.0469
			Testing	0.0727	0.0535	0.0784
		STDEV	Training	0.0252	0.0349	0.0253
			Testing	0.0315	0.0455	0.0261
Unit-2 (Case-3)	Expanded input and expanded output of first unit with bias to cascaded unit	MAPE	Training	5.3638	3.8547	3.4461
			Testing	5.9255	5.0693	3.6357
		RMSE	Training	0.0730	0.0499	0.0429
			Testing	0.0723	0.0523	0.0695
		STDEV	Training	0.0251	0.0346	0.0192
			Testing	0.0277	0.0388	0.0228

Best simulation results obtained corresponding to the developed model have been shown as bold values.

Table 7
Cascaded FLANN-PSO model with three different input combinations to cascaded unit using 10-fold cross validation.

PSO		Industry		Electronics	Garment	Metal & Machinery
Type and number of expansions in first unit		Power series with 3 number of expansions per input				
Type and number of expansions in cascaded unit		Power series with 3 number of expansions per input				
Unit-1	Expanded input with bias	MAPE	Training	5.4094	2.7504	2.8206
			Testing	5.4250	3.1888	3.2943
		RMSE	Training	0.0665	0.0367	0.0415
			Testing	0.0668	0.0819	0.0808
		STDEV	Training	0.0353	0.0212	0.0125
			Testing	0.0496	0.0338	0.0197
Unit-2 (Case-1)	Expanded output with bias to cascaded unit	MAPE	Training	**5.2839**	**2.3426**	**2.5571**
			Testing	**5.3210**	**2.7740**	**2.9129**
		RMSE	Training	**0.0472**	**0.0344**	**0.0413**
			Testing	**0.0581**	**0.0529**	**0.0767**
		STDEV	Training	**0.0303**	**0.0111**	**0.0127**
			Testing	**0.0425**	**0.0215**	**0.0168**
Unit-2 (Case-2)	Expanded input and expanded output of first unit to cascaded unit	MAPE	Training	5.3043	2.3733	2.6739
			Testing	5.3882	2.8857	3.1414
		RMSE	Training	0.0551	0.0352	0.0473
			Testing	0.0699	0.0623	0.0998
		STDEV	Training	0.0316	0.0212	0.0206
			Testing	0.0364	0.0223	0.0244
Unit-2 (Case-3)	Expanded input and expanded output of first unit with bias to cascaded unit	MAPE	Training	5.3995	2.3455	2.5927
			Testing	5.4103	2.7944	3.1244
		RMSE	Training	0.0543	0.0358	0.0457
			Testing	0.0686	0.0579	0.0599
		STDEV	Training	0.0344	0.0210	0.0168
			Testing	0.0480	0.0227	0.0192

Best simulation results obtained corresponding to the developed model have been shown as bold values.

the last case under consideration, output from the first unit, input pattern of the first unit and a bias signal are inputs for the second unit.

5.1.1. Analysis of single unit of models

The detailed structure of first unit of the model is shown in Fig. 5. $f(p,y)$ is the p^{th} element of the z element input pattern vector where y denotes an input pattern vector of L such input pattern vectors. $\hat{o}(y,t)$is the estimated number of new products of y^{th} input pattern vector during the t^{th} iteration. $d(y)$is the desired number of new products of y^{th} input pattern vector. $e(y,t)$ is the prediction error of the y^{th} input pattern vector during the t^{th} iteration. k is the length of the functional expansion for each element of the

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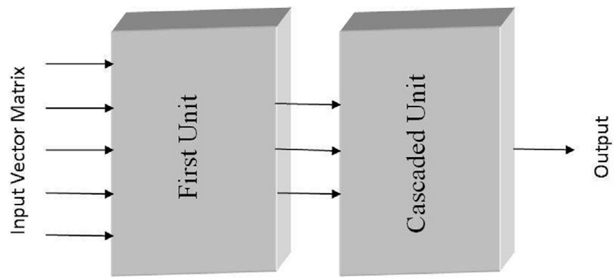

Fig. 3. Block diagram of cascaded network.

input pattern vector. $s_0(t),\ s_1(t), s_2(t), \ldots, s_{nk+1}(t)$ are the elements of the weight vector during the t^{th} iteration.

Let be theythinput pattern vector i.e.

$$F(y) = [f(1,y)f(2,y)f(3,y)\ldots\ \ldots\ \ldots\ \ldots\ \ldots\ f(z,y)] \quad (1)$$

And let $F^1(y)$ be the expanded input vector including bias input for the y^{th} input pattern vector i.e.

$$F^1(y) = [f^1(1,y)f^2(1,y)f^3(1,y)\ldots f^k(1,y)\ldots\ \ldots\ \ldots \\ f^1(z,y)f^2(z,y)f^3(z,y)\ldots f^k(z,y)1]$$

$$F'(y) = [f_1(y)f_2(y)f_3(y)f_4(y)f_5(y)\ldots\ \ldots\ \ldots\ \ldots\ \ldots\ \ldots \\ f_{zk}(y)f_{zk+1}(y)] \quad (2)$$

where $f_1 = f^1(1,y);\ f_2 = f^2(1,y);\ f_3 = f^3(1,y);\ldots\ \ldots\ \ldots;\ f_{nk} = f^k(z,y);\ f_{zk+1} = 1$

For z element input pattern vector, total number of elements formed is given by

$$Z = zk + 1 \quad (3)$$

And $S(t)$ be the weight vector during the t^{th} iteration i.e.

$$S(t) = [s(t)s_1(t)s_2(t)\ldots\ \ldots\ \ldots\ s_{zk}(t)s_{zk+1}(t)] \quad (4)$$

The estimated new products of the y^{th} input pattern vector during the t^{th} iteration is given by

$$\hat{o}(y,t) = F^1(y) * S^T(t) \quad (5)$$

$$\hat{o}(t,y) = \left(e^{o(t,y)} - e^{-o(t,y)}\right)/\left(e^{o(t,y)} + e^{-o(t,y)}\right) \quad (6)$$

And the prediction error for the y^{th} input pattern vector during the t^{th} iteration is

$$e(t,y) = \hat{o}(t,y) - d(y) \quad (7)$$

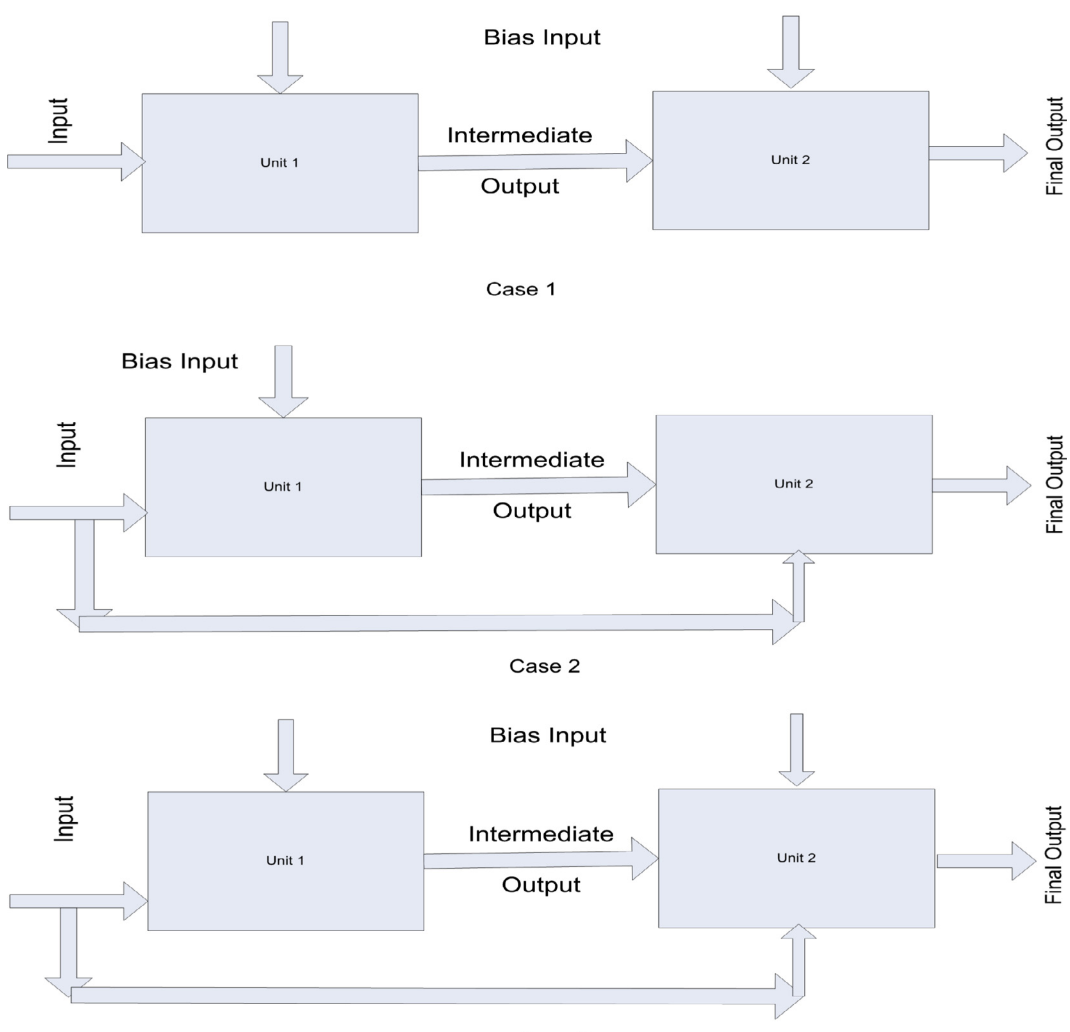

Fig. 4. Different Pattern developed on the basis of input combination to the cascaded unit.

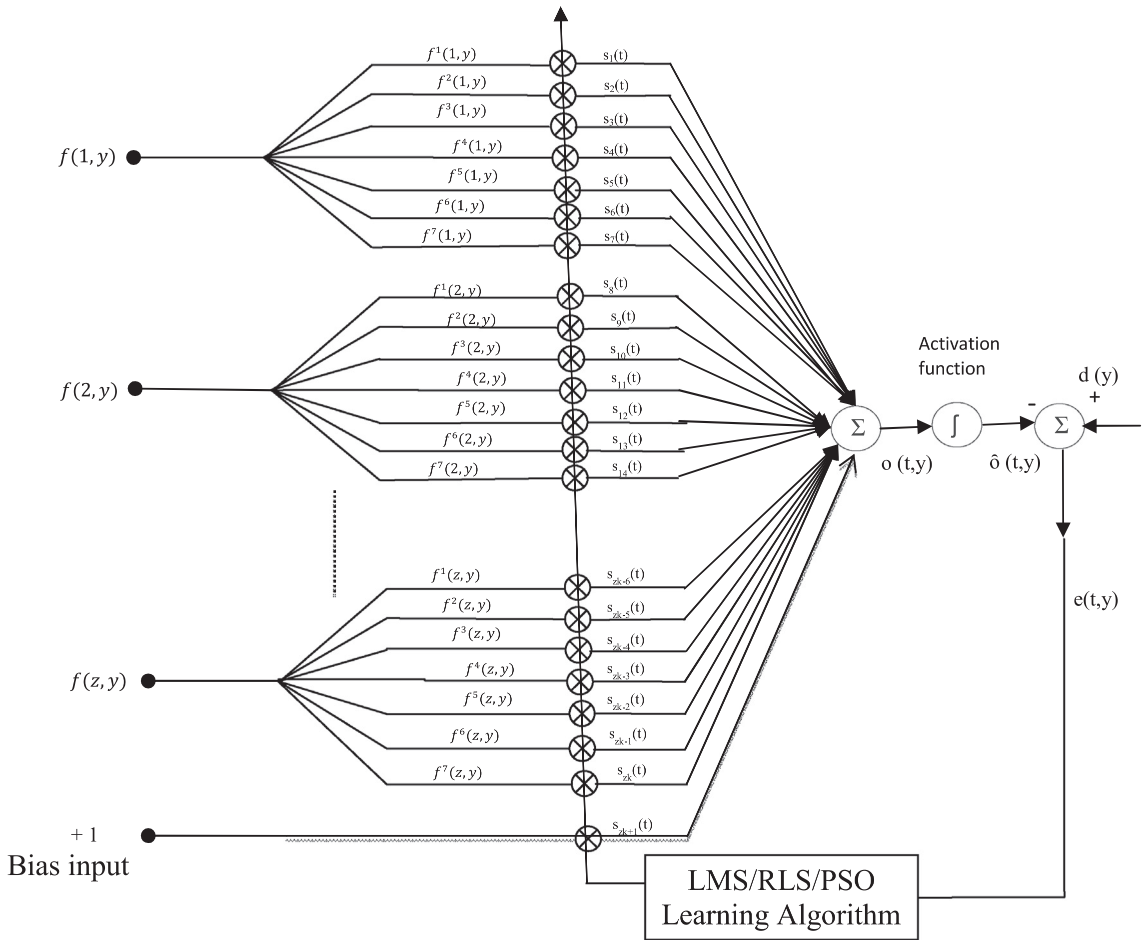

Fig. 5. FLANN model with power series expansion.

5.1.1.1. Training of the model by Least Mean Squares (LMS) Method (model-I). Let Q be the total number of input patterns applied to the model during training. For each iteration, these input patterns are applied in a sequential manner and the updating of weights is done at the end of the iteration by computing the average change in the weights over Q input patterns. These iterations are performed until *MSE* of the model attains steady state value. Let the total number of iterations be T.

Updating the j^{th} weight is done by computing the average change in the j^{th} weight over Q input patterns (Δs_j).

$$s_j(t+1) = s_j(t) + \Delta s_j(t);\ j = 1, 2, 3, \ldots \ldots, zk,\ zk+1 \tag{8}$$

Where

$$\Delta s_j(t) = \frac{\sum_{y=1}^{y=Q} \mu * f_j(y) * e(t,y)}{Q};\ \mu \text{ is the learning factor} \tag{9}$$

Eq. (9) can be derived using steepest descent algorithm.

Mean Square Error during the training period is given by

$$mse(t) = \frac{\sum_{y=1}^{y=Q} e^2(t,y)}{Q};\ t = 1, 2, 3, \ldots, T \tag{10}$$

The convergence rate and convergence value of the RMSE can be adjusted using the learning factor μ.

5.1.1.2. Training of the model by Recursive Least Squares (RLS) method (model-II). The cost function used in RLS method is sum of error squares up to that point i.e.,

$$\varepsilon_{y+1} = \sum_{j=1}^{y} \lambda^{y-j} |e(j)|^2 \tag{11}$$

(or)

$$\varepsilon_{y+1} = \varepsilon_y + |e(y)|^2 \tag{12}$$

where λ is the forgetting factor which is nearly equal to unity and

Optimal weight vector (S)at point$y+1$ minimising the cost function is given by

$$S(y+1) = A_{y+1}^{-1} * C_{y+1} \tag{13}$$

where Auto correlation vector (A) and Cross correlation vector (C) are given by

$$A_{y+1} = A_y + F'(y+1) * F'^T(y+1) \tag{14}$$

$$C_{y+1} = C_y + d(y+1) * F'^{(y+1)} \tag{15}$$

Updating the optimal weight vector at point y is done according to

$$S(y+1) = S(y) + \frac{e(y) * r(y)}{1 + g(y)} \tag{16}$$

Where

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$$r(y) = A_y^{-1} * F'^{(y)} \quad (17)$$

$$g(y) = F'^{T}(y).r(y) \quad (18)$$

And updating the auto correlation matrix (A) at point y is done according

$$A_{y+1}^{-1} = A_y^{-1} - \frac{r(y) * r^T(y)}{1 + g(y)} \quad (19)$$

The inverse autocorrelation matrix is initialised as $A_0^{-1} = \sigma^2 * I$, where σ^2 is of magnitude of $10^3 - 10^5$; I is an identity matrix of$N * N$dimensions where N is given by Eq. (3).

5.1.1.3. Training of the model by Particle Swarm Optimization (PSO) method(model-III). Let b be the number of particles with randomly defined local best positions (∂_b) and velocity $(\ddot{\upsilon}_b)$ used in the algorithm and for every bird the fitness function (τ) has been evaluated for getting the particle best position by giving L input pattern of training dataset on the basis of minimum error (e) between predicted and actual values using Eq. (7).

$$\tau_b = \min\ (e) \quad (20)$$

The input pattern for which τ_b is defined is taken as the particle best position parameters.

A comparison has been made for finding the global best position for particle between its present best position and local best position and the best fitted value is taken as the global best position. The particle velocity and position updating equation with respect to present position (δ_b) of particle is as follows

$$\ddot{\upsilon}_b = \ddot{\upsilon}_b + c1 * a\chi * (\partial_b - \delta_b) + c2 * a\chi * (\tau_b - \delta_b) \quad (21)$$

$$\delta_b = \delta_b + \ddot{\upsilon}_b \quad (22)$$

where, c1 and c2 are user defined constant values lying between 0 and 2; χ is a randomly generated number whose value lies in between 0 and 1.

5.1.2. Analysis of model with different combinations of input to cascaded unit

On the basis of connecting second (cascaded) unit to first unit; three different combinations have been implemented for the analysis. Flexibility in choosing first and cascaded unit as same or different is provided for the developed model. Option of independent numbers of expansions along with choice of functional expansion in first and cascaded unit has been provided as well. The developed model works efficiently and provides the best results if both the unit i.e. first and cascaded uses the same algorithm along with the same numbers of expansions and type of functional expansion. Results obtained from the analysis have been shown for the homogenous units and for same number of expansions in Tables 5, 6 and 7.

5.1.2.1. Case –I: Output from first unit and bias signal as input to cascaded unit. The output from first unit (it could be modeled with any of the LMS, RLS or PSO algorithm) $\hat{o}(t, y)$ (Eq. (6)) also defined as intermediate output (Fig. 3) is given to the cascaded unit as an input along with the bias signal (+1). Let k is the length of power function expansion then the input actually given to the cascaded unit is

$$\hat{o}(t, y) = \left[\hat{o}_1^1(t, y)\hat{o}_2^2(t, y) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .\hat{o}_k^k(t, y)1\right] \quad (23)$$

where 1 is the bias input signal

Rest of the steps are same as discussed above depending on the choice of unit selected as the cascaded unit.

5.1.2.2. Case –II: Input as well as output from the first unit are taken as input for cascaded unit. The input of the first unit is given as the input for second unit as well and on the place of bias signal output of the first unit is used as the final input vector given to the cascaded unit (using Eqs. (2) and (6))

$$\hat{o}(t, y) = [f_1(t, y)f_2(t, y)f_3(t, y)f_4(t, y)f_5(t, y) \ldots \ldots \ldots \ldots \ldots \ldots \ldots f_{zk}(t, y)\hat{o}(t, y)] \quad (24)$$

This input is provided to the cascaded unit for analysis

5.1.2.3. Case –III: Input and output of the first unit as well as bias signal is taken as input for cascaded unit. Input in this case is different from the input derived under case – II only by the bias signal. On adding bias signal to the Eq. (24) the input pattern generated will be given as the input to the cascaded unit taken care under this case

$$\hat{o}(t, y) = [f_1(t, y)f_2(t, y)f_3(t, y)f_4(t, y)f_5(t, y) \ldots \ldots \ldots \ldots \ldots \ldots \ldots f_{zk}(t, y)\hat{o}(t, y)1] \quad (25)$$

All these cases are shown in Fig. 3 and the input corresponding to different cases I, II and III are given by Eqs. (23), (24) and (25) respectively.

5.1.3. Model testing

Once the optimum weights were obtained, the model is set to provide its best performance and the model is tested with testing samples which have not been used for training. During testing, a known input pattern is applied to the model to estimate the known output. Mean value for the percentage ratio of absolute difference between estimated and known outputs to actual output is calculated and used as performance index of the model to gauge excellence of the model and is defined as

$$MAPE = \frac{1}{h}\sum_{j=1}^{j=h}\frac{|d(j) - \hat{o}(j)|}{d(j)} * 100 \quad (26)$$

Also, root mean square error and standard deviation values have been calculated using Eqs. (27) and (28) respectively.

$$RMSE = \sqrt{\frac{1}{h}\sum_{j=1}^{j=h}(d(j) - \hat{o}(j))^2} \quad (27)$$

$$STDEV = \sqrt{\frac{1}{h}\sum_{j=1}^{j=h}(\bar{\mathrm{d}}(\mathrm{j}) - \hat{o}(j))^2} \quad (28)$$

where h is total number of input patterns utilized during testing phase of developed models; d(j) and $\bar{d}(j)$ are desired and estimated values respectively. $\bar{d}$(j) is the mean value of the actual output values considered for computation.

5.1.4. Parameters used in model development

Parameters used in different configuration of FLANN with LMS, RLS and PSO feedback algorithms have been provided in the Tables 2, 3 and 4 respectively.

6. Multiple linear regression

Regression was first coined by Galton (1885) while discussing the height of humans. Concept of multiple linear regression (MLR) was given by pearson in 1908 (Inc, 2016). Multiple linear regression is a statistical technique which is used to find the linear relationship between number of factors affecting the particular phenomenon. Different variant of this technique could be used to works with both continuous and categorical variables. MLR tech-

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nique has found numerous applications belonging to different fields and many empirical studies have been made using this concept. Zare Abyaneh (2014) has made a comparative study in predicting the water quality parameters using multiple linear regression (MLR) and artificial neural network (ANN). Predicting river flow using ANN and MLR models by Noori et al. (2010). Comparison of neural networks and regression technique for ozone forecasting by Comrie (1997). Traffic forecasting for shorter period by Sun et al. (2002). Electricity consumption forecasting using linear regression by Bianco et al. (2013). Ordinary least square estimation technique has been used as a method for finding the coefficient and intercept/constant values under multiple linear regression and accordingly equations have been formulated.

Multivariate Linear regression is a statistical method of mapping the phenomenon using different factors those believed to be the cause for that. The critical factors considered for the study are taken as input and modelled in the form of linear regression as follows

$$\hat{o}(y) = Þ_1 f(1,y) + Þ_2 f(2,y) + \dots \dots \dots \dots \dots \dots \dots + P_k f(k,y) + \quad (29)$$

where $Þ_1$ to $Þ_k$ are constant coefficient values, Є is the random error or intercept and x is the input data vector for y^{th} row sequence from the input matrix containing values of different critical factors.

In matrix form Eq. (29) is written as

$$\hat{O} = FÞ + \epsilon \quad (30)$$

where $\hat{O}$, F, Þ and ϵ are of $(n \times 1)$, $(n \times k)$, $(k \times 1)$ and $(n \times 1)$ dimensions matrix respectively.

Coefficient values are estimated by ordinary least square algorithm using the Moore-Penrose pseudo inverse technique as follows

$$Þ = \left(X^T X\right)^{-1} X^T \hat{Y} \quad (31)$$

$$R^2 = 1 - \left(\frac{SS_r}{SS_t}\right) \quad (32)$$

$$Adjusted\ R^2 = 1 - \left(\frac{\frac{SS_r}{DF_r}}{\frac{SS_t}{DF_t}}\right) \quad (33)$$

where, SS denotes sum of square; DF denotes degree of freedom; r signifies residual terms; t signifies total number of terms.

The performance of this model has been estimated using the R^2 and adjusted R^2 value. Also significant p-values show the importance of factors in mapping the observed phenomenon.

Table 8
Multiple linear regression statistics obtained for three industries.

Independent Variables	Coefficient value	t-value	Sig.
(a). Electronics Industry			
Intercept / Constant value	−0.850	−17.772	**0.000**
Number of permanent employees	0.020	1.163	0.246
Gross National Income of country where firm operates	−0.017	−0.534	0.594
Years completed after establishment	8.582E−5	0.005	0.996
Experience of exporting in years	−0.002	−0.169	0.866
Percentage of supplies from domestic market	−0.003	−0.386	0.699
Total number of products produced	0.072	2.177	**0.030**
Technology used for production	−0.017	−1.821	0.070
R&D expenditure in one year	−0.014	−0.453	0.651
Sales amount realized in one year	0.037	2.028	**0.043**
(b) Garment Industry			
Intercept / Constant value	−0.879	−50.646	**0.000**
Number of Permanent Employees	0.002	0.191	0.849
Gross National Income of country where firm operates	0.009	2.520	**0.012**
Years completed after establishment	−0.004	−0.543	0.587
Experience of exporting in years	0.001	0.258	0.796
Percentage of supplies from domestic market	0.001	0.282	0.778
Total number of products produced	0.114	7.817	**0.000**
Technology used for production	0.002	1.082	0.280
R&D expenditure in one year	0.001	0.080	0.936
Sales amount realized in one year	−0.001	−0.136	0.892
(c) Metal & Machinery Industry			
Intercept / Constant value	−0.910	−36.280	**0.000**
Number of permanent employees	−0.016	−0.922	0.357
Gross National Income of country where firm operates	−0.003	−0.348	0.728
Years completed after establishment	−0.015	−1.867	0.063
Experience of exporting in years	−0.009	−1.410	0.159
Percentage of supplies from domestic market	−0.003	−0.786	0.432
Total number of products produced	0.069	3.944	**0.000**
Technology used for production	−0.002	−0.419	0.676
R&D expenditure in one year	−0.013	−0.847	0.397
Sales amount realized in one year	0.037	2.963	**0.003**

*Dependent Variable: Number of new products
Independent variables affecting the output of regression model significantly are shown as bold values.

Table 9
R square and adjusted R square values value for multivariate linear regression.

Industry	R square value	Adjusted R square value
Electronics	0.081	0.055
Garment	0.144	0.126
Metal & Machinery	0.068	0.050

7. Results

Output obtained from the analysis for different developed models are tabulated in Tables 5, 6, 7, 8 and 9. Tables 5, 6, and 7 show the performance of simple and cascaded neural networks under different configurations for three different industries in term of RMSE and MAPE. Tables 8 and 9 show the output obtained of multiple linear regression model in term of significance level of the variables used in the analysis and R-squared values respectively.

The best results were obtained with PSO weight updating algorithm. PSO is a nature inspired technique developed by observing natural phenomenon happening on daily basis. It is evolved by studying the flying pattern of birds in a group without any collision. Since PSO itself evolved from natural phenomenon it is expected that it may converge for other real time problems as well more efficiently than its counterpart algorithms.

8. Interpretation of results

Best result has obtained for the cascaded model which has been configured as case-1 of unit-2 for all the cases under consideration. In case-1 of unit-2 output of unit-1 has been expanded using power series functional expansion with same numbers of expansion terms as used in unit-1 and given to the cascaded unit plus the bias signal. It provides the minimum value for MAPE and RMSE as compared to other configurations used for the analysis. RMSE suggests convergence capability of the model; lower RMSE value means better convergence. Lower MAPE value signifies lesser difference between actual and predicted values obtained using developed model which result in better prediction accuracy of the model.

Results obtained shows that FLANN with PSO is the best performing cascaded neural networks whereas FLANN with LMS and

Table 10
Comparison of previous studies with present investigation.

Sl. No.	Type of data set	Size of data set	Algorithm used	Performance Index
1.	Ekbatan waste-water treatment plant, Tehran, Iran (Zare Abyaneh, 2014)	84	Regression and MLANN	37.8 (RMSE-Regression) 25.1 (RMSE-MLANN)
2.	Exchange rate (Majhi et al., 2006)	365	FLANN-LMS	3.1 (APE)*
3.	Exchange rate (Majhi et al., 2009)	418	Cascaded FLANN	1.9 (APE)*
4.	Electrical load and weather (AlFuhaid et al., 1997)	365	Cascaded ANN	2.707 (MAPE)
5.	Electricity consumption (Bianco et al., 2013)	37	Linear Regression	0.981 (Adj. R^2)
6.	Ozone and weather U.S. database (Comrie, 1997)	690	Regression and MLANN	0.59 (R^2) and 7.01 (MAE)**
7.	England market energy clearing price (Zhang et al., 2003)	31	Cascaded ANN	6.27 (MAPE)
8.	Monthly rainfall, discharge, sun radiation and temperature	216	Regression and MLANN	0.79 (Adj. R^2) and 1.06 (MAE)**
9.	Electronics industry (Present investigation)	327	Cascaded PSO	5.3210 (MAPE)
10.	Garment industry (Present investigation)	445	Cascaded PSO	2.7740 (MAPE)
11.	Metal and machinery industry (Present investigation)	464	Cascaded PSO	2.9129 (MAPE)

Note: *APE stands for Average Percentage Error, **MAE stands for Mean Absolute Error

RLS shows minor improvement over each other for specific industry.

On the other hand, multiple linear regression is not able to track down the trend of launching new products follows by the industries considered under this study. It is clearly visible from the significance values mentioned in Table 8 that most of the critically important variables were coming as insignificant variables for analysis. The criterion for variable to be considered as significant is that its p-value or significance value should lies in between 0 and 0.05 which means it should meet the criteria of 95% confidence interval. For electronics industry intercept / constant value, total number of products produced and sales amount realized in a year have came as significant variables. In case of garment industry along with intercept / constant, total numbers of products produced and gross national income of the country where firm operates were came as significant and for metal & machinery industry intercept / constant, total numbers of products produced and total sales amount realized in a year considered to be significant variables. As in multiple linear regression analysis we found that most of the critically important variables were came out as insignificant in prediction which suggests that production of new products is a phenomenon which is non linearly associated with many direct and indirect (latent) variables. As linear regression can track only linearly related phenomenon; it does not able to track the trend of new products production which is evident by small value of R-square and adjusted R-square. R-square is the percentage of variance explained considering all the independent variable as significantly contributing and adjusted R square value is calculated by considering only those variables which are actually affecting the phenomenon.

FLANN has inherent non-linearity in its structure and thus handled the phenomenon better which is evident from the result statistics. PSO as weight updating algorithm provides the results with the highest accuracy as compared to other algorithms implemented.

9. Conclusion

Developing new products is a non-linear phenomenon with respect to many parameters and could not be tracked using multiple linear regression. Techniques having inherent non-linearity or may induce non-linearity would be useful in estimating successful numbers of new products to be launched. Artificial neural networks inherent non-linearity in their structure and hence able to tracked down the changes. It is observed that cascading of network makes the network more efficient than its parent unit but at the cost of more computational load and complex structure. The PSO algorithm which is actually a nature inspired technique and comparatively newer than LMS and RLS algorithms performs better and the cascade arrangement makes PSO even more efficient. Table 10 shows the type as well as size of the data set used in measuring the performance of different models implemented in previous studies.

10. Managerial implications

This paper tried to predict the numbers of new products that a firm should launch to remain competitive and profitable in the market. This will help the managers to manage inventories and other resources. It may also help in making strategically important decisions for the firm. Moreover, wastages could be reduced which means cost effectiveness without compromising on the quality of the product. Different factors influencing production could be identified by managers those are firm specific (smaller firms may have different requirement as compared to large firms in the same way technologically advanced firms may have different strengths rather than labor intensive firms).

Revenue generation for sales is one of the most important factors for determination of production of new products and by knowing the previous trends upcoming sales revenue may be forecasted helping manager to study the market scenario. Database maintained for different parameters related to new products could be used to map different cause effect relationships as well.

11. Directions for future work

Prediction of new products is a complex phenomenon which depends on many factors those are industry specific and difficult to measure directly. It may be possible to increase the efficiency of developed models by identifying and adding some other critically important parameter in the analysis. By exploring maximum of latent variables better results could be expected. Increasing sample size may be helpful in generalizing the trend for efficient prediction by the developed models.

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